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Quality Risk and Profitability in Cattle Production: A Multivariate Approach

Eric J. Belasco, Ted C. Schroeder, and Barry K. Goodwin

This study evaluates quality, production, and price risk within the context of overall profit variability in fed cattle production. The approach used offers a flexible way to estimate a large system of equations with more than three jointly related censored outcomes. Trade-offs between quality and yield grade levels and production measures, such as average daily gain and feeding efficiency, are evaluated. Simulation procedures are used to assess the impact of quality risk on overall profit variability. Results make an important contribution to existing research by explaining why price signals through grid quality grade premiums may not generate intended producer responses.

Key Words: censoring, copula, fed cattle, grid pricing, multivariate, quality risk

Introduction

Agricultural producers operate and make ex ante decisions that are based on uncertain price and quality outcomes, introducing risk into most decisions. This uncertainty has led to a large body of research examining the efficacy of jointly managing price and yield risk (e.g., Goodwin and Ker, 2001). However, there are many instances when price itself is a function of the production process. This additional variability in price is due to premiums or discounts that are given to high- and low-quality items and add a new dimension to overall profit variability in the form of quality risk. The objective of this study is to evaluate cattle carcass quality risk within the context of overall cattle-feeding profit variability while providing a general framework for assessing quality, price, and yield risk factors.[1]

This study makes three important contributions to our current understanding of risk in cattle feeding. First, we provide a flexible approach for incorporating quality risk into production risk using copulas, which can be widely applied in production economics. A copula-based approach allows us to explicitly specify the covariance structure independent of each marginal distribution and accommodates for the high-dimensionality, high degree of correlation, and number of censored variables in this application. To our knowledge, this is the first study that uses copulas to identify parameters within a system of equations containing more than three censored dependent variables.

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[1] Factors such as genetics, breed, and frame size are treated as stochastic variation in this research study; however, it is acknowledged that such factors are often observable to cattlemen. Nevertheless, because we are not evaluating cattlemen's expectations regarding profitability, conditional on variables unknown in this research, we assume those factors to be independently and normally distributed.

Second, this study explicitly examines trade-offs between quality and yield risk components in cattle feeding. By focusing on the covariance structure, we are able to assess the nonlinear trade-offs between quality grade, yield grade, and performance measures (e.g., average daily gain and feed conversion rates). Within certain ranges, incentives to produce higher quality grades may counteract incentives to maximize feed conversion efficiency. This study evaluates the severity of this trade-off. From a producer's perspective, it is important to know if and when it is worth accepting poorer feeding performance in order to attain a higher quality grade and receive a premium. It is hypothesized that the trade-off partially obstructs signals for higher quality grades from packers to the producer.

Third, simulations allow for an assessment of the impact of quality risk on overall profit variability based on any grid pricing structure. Past studies have anecdotally mentioned that the inclusion of quality risk into livestock marketing increases overall profit variability. However, the amount of added risk has not been explicitly identified. Although quality risk components add variability to profit, a negative correlation between quality grades and production variables would mitigate a portion of that risk. This is analogous to joint distributions used in revenue-based crop insurance products where the negative correlation between crop yields and prices reduces total revenue variability. In the example of corn, the reduction to revenue risk occurs because lower yields usually result in higher prices. This is the first study to explicitly consider these trade-offs in order to effectively identify the impact of grid pricing on profit variability.

To account for the dynamic and nonstandard grid pricing structure, this study uses the weekly grid premium and discount price report from the USDA's Agricultural Marketing Service (AMS) to generate an average grid.[2] While each simulation makes an assumption about the grid premiums and discounts, these assumptions are easily adjusted to assess the robustness of our results to alternative grid structures. This study also utilizes feedlot data on 7,706 pens of cattle that were priced on a grid in western Kansas and Nebraska. The data contain the percentage of weight within each yield and quality grade, as well as cattle production performance variables.

Review of Literature and Methods

A recent study by Zago (2009) examined the trade-off between quality and quantity in the production of wine grapes and argued that quality and quantity are substitutes for each other. Other products that are priced based on quality include vegetables, fruits, cotton, and meat. Meat quality is based on standardized USDA grading standards, where carcass quality is based largely on marbling for fed steers and heifers and meat yield is an estimate of the red meat yield of a carcass. Within each quality category, there is a premium or discount that is determined at the consumer level in each market.[3] The recipient of this premium or discount internalizes the rewards or penalties associated with quality. In an attempt to improve the level of meat quality, the beef industry adopted grid pricing, which transferred meat quality risk from the beef packer to the livestock producer. This move was motivated in part by the reality that the end of the supply chain is largely constrained in its ability to influence quality.

[2] The USDA/AMS publishes a weekly report, titled "National Carcass Premiums and Discounts for Slaughter Steers and Heifers," which collects reported premiums and discounts from firms in the meat packing industry on a weekly basis and computes the national average of premiums/discounts associated with all quality and yield grades.

[3] Some discounts, such as those given to excessively light and heavy carcass weights, are provided due to the additional costs associated with production and not necessarily due to the loss in value to consumers.

The only way to improve end-use quality is by providing appropriate signals to feeder cattle producers (Vanek, Watts, and Brester, 2008). These signals can help promote higher quality by providing incentives for investment in genetic programs or adjustments in feed management aimed to increase meat quality.

The profit function for a producer who internalizes quality risk can be written as:

$$\pi\left(p^y, p^p, p^i, x_1, x_2\right) = pf(x_1) - c\left(p^i, x_2\right), \tag{1}$$

where $p = p^y + p^p$ such that p is the realized output price, p^y is the average output price without any quality considerations, and p^p is a premium or discount associated with quality. Further, p^i is the price of inputs x_2, while inputs x_1 are transformed into outputs through some production function captured by $f(\cdot)$.[4] In the case of stable prices, producers optimize while jointly considering the quantity and quality of the output. The idea behind grid pricing is to provide incentives to produce higher quality meat.[5]

In the case of grid pricing, p^y, p^p, and p^i from equation (1) are, respectively, fed cattle prices, quality premiums, and input prices (corn), which all exhibit temporal variation. The production function $f(x_1)$ has inputs of corn as well as parameters that define weight gain efficiency, typically measured as average daily gain. This production function has multiple outputs that include the amount and quality of the output. Costs are primarily determined by the price of inputs such as feeder cattle and corn, as well as the efficiency of cattle in converting feed into weight gain. Costs may also be determined by health factors such as payments for veterinary services and mortality losses.

Past research regarding grid pricing has focused on two main areas: (*a*) the efficiency of marketing channels under grid pricing, and (*b*) the impact on cattle producer profitability under grid pricing as opposed to average weight pricing, where returns to cattle owners are based on average weight for the entire pen. Theory suggests average pricing mechanisms may distort the market by not providing clear signals about consumer preferences to upstream producers. Empirical evidence suggests value signals are not effectively transmitted to producers when average pricing systems are used (Fausti, Qasmi, and Li, 2009; Anderson and Zeuli, 2001).

Risk in cattle production is comprised of temporal variation in input and output prices as well as cross-sectional variability in production. Under grid pricing, fed cattle carcass quality risk is a component of overall profit variability. Cattle production performance variables, which include average daily gain, feed conversion rates, mortality rates, and veterinary costs, are highly correlated with one another (Belasco, Ghosh, and Goodwin, 2009). Furthermore, five yield grades (1, 2, 3, 4, 5), five quality grades (Prime, Upper Choice, Lower Choice,[6] Select, Standard), and three additional discounted measures [Dark Cutters, Heavy (>950 lbs.), and Light (<550 lbs.)] are also correlated with one another and with production performance measures. The high degree of dimensionality is one major obstacle in evaluating overall profit variability involving pricing on a grid.

[4] Different subscripts are used for x to indicate that these inputs need not all be the same. While some components, such as fertilizer, may impact both sides of the equation, others may impact only one side. An example of the latter may be fuel, which is a cost, but doesn't cause an increase to production. Likewise, weather may improve yields but not be associated with any direct costs.

[5] It is important to note that incentives from packers can vary because different market segments demanding different qualities of meat are targeted. As a reviewer pointed out, some packers more aggressively pursue some markets and utilize grids to provide incentives directed toward that market segment.

[6] Upper and Lower Choice are the top two-thirds and bottom one-third of Choice, respectively.

Grid Pricing Structure

A value-based pricing system that rewards high-quality meat and punishes low quality was first recommended as a major marketing alternative for fed cattle in 1990. The main idea behind this marketing system was to encourage beef packers to provide stronger signals to producers regarding increasing demand for high-quality meat products. As Fausti, Qasmi, and Diersen (2008) point out, average pricing mechanisms result in market inefficiency since the highest returns are given for additional carcass weight, regardless of quality. However, since consumers are willing to pay premiums for higher quality cuts of meat and producers can adapt strategies and technology to meet this demand when given enough incentive, quality premiums need to be sent back to the producer (Schroeder et al., 1998).

Although there are many different grid pricing structures, most provide a base price for which there is no discount or premium. For carcasses that grade above (below) Lower Choice or yield grade 3, premiums (discounts) are incurred by the cattle owner. In this way, the pricing structure more closely reflects what the meat will be worth at the consumer level. Quality risk under grid pricing is internalized by the producer. An example grid structure, which has similar discounts and premiums to the grid calculated by Pyatt et al. (2005), is shown in table 1.[7]

While grid pricing systems became more popular throughout the late 1990s, grid pricing use has been relatively stable since 2001 (Fausti, Qasmi, and Diersen, 2008). Fausti, Qasmi, and Li (2009) use Granger causality tests to support their hypothesis that signals from packers to producers are not efficiently transmitted. Many studies have made similar observations about this poor signal (e.g., Johnson and Ward, 2005; Schroeder and Graff, 2000), yet few studies have focused on the reasons for this inefficiency.

Rahman (2006) concludes heavy penalties associated with low-quality carcasses outweigh the premiums associated with high-quality carcasses, which may discourage producers from more fully utilizing grid pricing. Other papers have concluded that the additional risk associated with quality may be a limiting factor to wider adoption (Anderson and Zeuli, 2001; Fausti and Feuz, 1995). Further, McDonald and Schroeder (2003) note that profit-maximizing cattle feeders must jointly manage costs, cattle performance, and carcass attributes. They estimate grid pricing risk to amount to 15% of overall profit variability. Many past studies focusing on cattle-feeding profits have only considered the average pricing of cattle (e.g., Belasco, 2008; Mark, Schroeder, and Jones, 2000; Lawrence, Wang, and Loy, 1999). This study evaluates overall cattle-feeding profit variability by incorporating quality risk into profitability risk. An essential step in this process is to accurately determine the relationship between grid (quality) and production (weight) components.

One challenge in such research concerns managing a large system of correlated random variables. With the inclusion of quality risk, we add the uncertainty of carcass weight to each of five yield grades, five quality grades, and three additional discount factors. As shown in table 1, this implies that a single pen of cattle can have some proportion of carcass weight graded into all or some of 28 yield/grade/discount category combinations. The percentage of total carcass weight classified into each quality and yield grade category is hypothesized to be partially determined by a set of ex ante pen-level characteristics, such as gender, entry weight, location, and time of placement. As Anderson and Zeuli (2001) emphasize, it is also important

[7] Values in this table are based on forecasted weekly grid prices for the simulated end date and are explained further in the "Estimation and Results" section.

Table 1. An Example Grid Pricing Structure ($/cwt carcass)

		Yield Grade				
Quality Grade		1	2	3	4	5
Prime		10.80	9.10	7.81	−4.12	−11.44
Upper Choice		5.12	3.42	2.13	−9.80	−17.12
Lower Choice		2.99	1.29	Base	−11.93	−19.25
Select		−5.61	−7.31	−8.60	−20.53	−27.85
Standard		−16.64	−18.34	−19.63	−31.56	−38.88
Light (carcass < 550 lbs.)	−20.35					
Heavy (carcass > 900 lbs.)	−11.69					
Dark Cutters	−31.71					

to characterize the correlations between grid and quality category placement. This research determines the impact of carcass quality risk in cattle-feeding operations. The hypothesis posited is that an important component of grid pricing adoption is the trade-off between quality and production payoffs.

Methodology

The objective of this study is to simulate ex ante profits for cattle feeding when allowing for grid pricing. We consider all elements of profit variability, which include yield and quality risk, corn and cattle price risk, and production risk. Quality and yield grade risk associated with grid pricing introduces 13 new conditionally stochastic components of risk to cattle production that have not been previously modeled. Quality premiums or discounts are based on prices associated with each grade and the amount of carcass weight achieving that grade.

More specifically, we define the following system of equations such that:

$$\begin{bmatrix} \mathbf{P} \\ \mathbf{Y} \\ \mathbf{Q} \\ \mathbf{D} \end{bmatrix}_i = \mathbf{x}_{1i} * \boldsymbol{\beta} + \boldsymbol{\varepsilon}_i , \tag{2}$$

where $\mathbf{P}_i$ is a $\{4 \times 1\}$ vector of performance variable outcomes which include average daily gain (*ADG*), the log of dry matter feed conversion rate (*DMFC*), mortality rate (*MORT*), and the log of veterinary costs (*VCPH*). $\mathbf{Y}_i$ is a $\{5 \times 1\}$ vector containing the proportion of weight placed into yield grades 1–5. $\mathbf{Q}_i$ is a $\{5 \times 1\}$ vector containing the proportion of weight placed into quality grades that include *Prime*, *Upper Choice*, *Lower Choice*, *Select*, and *Standard*. $\mathbf{D}_i$ is a $\{3 \times 1\}$ vector that includes discount factor realizations such as *Dark Cutters* and *Light* or *Heavy* weight carcasses. A $\{17 \times 8\}$ matrix of conditioning variables, $\mathbf{x}_{1i}$, influences the mean of each dependent variable and includes the log of average placement weight (lbs.) and binary variables to indicate location, placement season, and gender.[8]

The errors in the above system of equations are likely to be heteroskedastic (Belasco et al., 2009; Belasco, Ghosh, and Goodwin, 2009). To control for this error structure, we assume a multiplicative conditional variance structure, such that $\varepsilon_{ij} \sim N(0, \sigma_{ij}^2)$, where $\sigma_{ij}^2 = f(\mathbf{x}_{1i}) =$

[8] Since each equation uses the same set of regressors, $\mathbf{x}_{1i}$ has 17 $\{1 \times 8\}$ vectors stacked atop one another.

$\exp(\mathbf{x}_{1i}\gamma_j)$ for each equation j. Maximum-likelihood estimation can be used to compute each conditional marginal distribution. However, nearly half of the dependent variables in the system of equations are censored. For example, only 45% of the pens in our sample contain carcasses that graded Prime.

A random variable y, which is left censored, can be expressed as a function of a latent variable y^*, with censoring point c, such that $y = y^*$ only when $y^* \geq c$, and $y = c$ when $y^* < c$. The censoring point is generally at zero, but can be set at any value. In order to account for censoring, we estimate using the Tobit model assuming multiplicative heteroskedasticity. Accounting for heteroskedasticity when present in a Tobit model is especially important because otherwise estimates are biased (Hurd, 1979).

We also assume residuals are correlated across equations based on the findings of Belasco, Ghosh, and Goodwin (2009). Their strategy for managing cross-equation correlations was to use a multivariate Tobit model with structure imposed on the off-diagonal covariance terms. However, their study concerned only a single censored variable. As cautioned by Chavas and Kim (2004), a system of equations containing more than three censored dependent variables cannot be identified using maximum-likelihood estimation. This limitation of traditional estimation methods motivates the use of copulas to characterize the covariate relationship between dependent variables. A major advantage of using a copula function is the flexibility with which conditional marginal densities can be independently defined. In this case, we model noncensored equations using a normal distribution while censored equations assume a Tobit model. Copula applications have been widely used in finance (Cherubini, Luciano, and Vecchiato, 2004), crop insurance (Zhu, Ghosh, and Goodwin, 2008; Vedenov, 2008), and weather risk (Filler et al., 2009) research.

The underlying idea behind a copula is that a joint distribution can be derived as the product of marginal densities and a unique copula function as:

$$(3) \qquad f(y_1, y_2, \ldots, y_m) = C\left(\alpha; F_1(y_1), F_2(y_2), \ldots, F_m(y_m)\right) \prod_{j=1}^{m} f_j(\beta_j, \gamma_j; x_j),$$

where there are m equations, each defined with an appropriate marginal density $f(\cdot)$, and a copula function $C(\cdot)$, which relates each of the marginal density functions. Copulas present a flexible way to estimate a system of equations that explicitly characterize the covariance relationship between conditional random variables. This is particularly important in simulating ex ante profits so that correlation between equations can be preserved.

As the number of equations increases, the simultaneous optimization of the marginal parameters (β, γ) and copula parameters (α) exponentially increases in complexity.[9] In this study, we estimate 17 equations and 136 parameters in α, given that the copula function will be a symmetric $\{17 \times 17\}$ matrix with ones along the diagonal.

Joe and Xu (1996) show that a two-stage estimator known as the inference function for margins (IFM), which is more computationally tractable, can be used to obtain consistent copula estimates. Given that the log-likelihood function of the joint distribution can be written with the marginals and copula function as additively separable, Joe and Xu propose first estimating each marginal density to obtain marginal parameters, followed by estimation of the copula function using the marginal parameter estimates. To illustrate, the log-likelihood function derived from equation (3) can be written as:

[9] Using an unstructured dispersion matrix that allows for each parameter to characterize the relationship between two inverse marginal functions, the dimension of the copula parameters increases with the dimension of equations, such that $\dim(\alpha) = (m^2 - m)/2$, where m is the number of equations.

(4)
$$\mathrm{Ln\,L} = \sum_{i=1}^{n} \log\Big[C\big(\alpha; F_1(y_{1i}), F_2(y_{2i}), ..., F_m(y_m)\big)\Big] + \sum_{i=1}^{n}\sum_{j=1}^{m} \log\Big[f_j(\beta_j, \gamma_j; x_j)\Big],$$

where it can be deduced that $\hat{\alpha}$ and $(\hat{\beta}, \hat{\gamma})$ are estimated by maximizing the first and second components of equation (4) separately. Shih and Louis (1995) employ a similar method to characterize a joint density function with censored data.

Joe and Xu (1996) suggest the use of the jackknife method of deriving asymptotically consistent standard errors when using the IFM approach. One criticism of the typical delete-one jackknife method is that it is computationally time-consuming in large samples. To provide computationally tractable standard errors, we use a block jackknife method that estimates a set of parameters after repeatedly eliminating a block of data, rather than a single observation (as in the typical jackknife method). Standard errors are then computed based on:

(5)
$$se(\hat{\beta}) = \sqrt{\sum_{k=1}^{g} \left(\tilde{\beta}^{(k)} - \bar{\tilde{\beta}}\right)^2},$$

where $\tilde{\beta}^{(k)}$ is the parameter estimate for β after eliminating block k from the data and $\bar{\tilde{\beta}}$ is the average across all $\tilde{\beta}^{(k)}$. Each block is estimated after eliminating 300 randomly determined observations and is repeated 25 times in order to derive a single block jackknife standard error. We repeat this process eight times and take the average standard error over the eight replications to identify a robust standard error estimate.

To specify the copula function, we must first invert the marginal density to recover the ranked ordering of the residuals. In the case of the normal distribution, this is rather straightforward, since the ranked ordering is realized by taking the cumulative density value for the given residual. Trivedi and Zimmer (2005) point out that the probability density function and the cumulative density function for the Tobit model can be respectively written as:

(6)
$$f_j\left(y_{ij} \mid x_i\beta_j\right) = \prod_{y_{ij}=0}\left[1-\Phi\left(\frac{x_i\beta_j}{\sigma_{ij}}\right)\right]\prod_{y_{ij}>0}\phi\left(\frac{y_{ij}-x_i\beta_j}{\sigma_{ij}}\right) \text{ and}$$

(7)
$$F_j\left(y_{ij} \mid x_i\beta_j\right) = \prod_{y_{ij}=0}\left[1-\Phi\left(\frac{x_i\beta_j}{\sigma_{ij}}\right)\right]\prod_{y_{ij}>0}\Phi\left(\frac{y_{ij}-x_i\beta_j}{\sigma_{ij}}\right)$$

for each censored equation, which for our purposes will include $j = 1, \dots, 10$. The cumulative and probabilistic normal density functions are denoted by Φ and ϕ, respectively.

The copula function can be estimated once the marginal residuals (ε_i) are inverted to a uniform distribution between 0 and 1, which can be expressed as $q_i = F^{-1}(\varepsilon_i)$. In the case of a Gaussian copula, Yan (2007) shows it can be simplified where:

(8)
$$C(\alpha; q_1, ..., q_m) = |\,\mathbf{\Sigma}(\alpha)\,|^{-1/2} \exp\left\{\frac{1}{2}\, q'\left(I_m - \mathbf{\Sigma}(\alpha)^{-1}\right) q\right\},$$

when $q = (q_1, ..., q_m)$ and $\Sigma(\alpha)$ is a symmetric dispersion matrix with parameters α. We use a Gaussian copula to relate the set of equations, thereby allowing us to maintain the correlation in simulation.[10]

Data

Proprietary cost and production data were obtained from five feedlots in Kansas and Nebraska that use grid pricing as a major marketing component. After deleting pens with average weight lower than 500 pounds or greater than 1,000 pounds, 7,706 pens of cattle with an average of 134 head per pen remained for our study sample. Each pen was accounted for at the initial and ending stages. As feeder cattle entered each feedlot, each pen was weighed and characteristics such as gender and placement date were recorded. At the end of the feeding period, performance measures were computed by weighing each pen and calculating costs, feed use, and mortalities. The quality and yield grades of each pen were recorded during the slaughtering process and were measured as percentages of total carcass weight. Thus, proportions of weight within yield grades 1–5 sum to one, as do proportions of weight within quality grades.

Figure 1 displays histograms associated with each quality grade category. Prime, Upper Choice, and Standard categories all exhibit large degrees of censoring with ranges of 55%, 15%, and 85%, respectively. Both Lower Choice and Select categories appear to be normally distributed with wide ranges between 0% and 100%. Similarly, yield grades 1, 4, and 5 are censored for 1%, 21%, and 83% of observations, respectively.

Table 2 reports summary statistics. Many of the variables exhibit censoring with a few variables being almost entirely censored—such as poor grades including *PctYG*5 and *PctStandard* with a degree of censoring over 80%. Alternatively, there are other variables which exhibit only a few observations at a censoring point (*PctYG*2, *PctYG*3, *PctSelect*).

Estimation and Results

In this section, we analyze production and quality risk through the estimation of marginal densities and use a copula procedure to preserve joint distributional properties and obtain asymptotically-consistent standard errors. Results allow us to evaluate the impact of independent variables on the mean and variance of each marginal density as well as to evaluate the covariance structure that characterizes the trade-off between quality and risk components. The subsection below estimates the three elements of price risk, which include premiums, corn prices, and cattle prices. The final subsection focuses on compiling all aspects of risk into a multivariate simulation to evaluate the impact of quality on overall profit variability.

Production Risk

Mean and variance parameter estimates for each marginal distribution are reported in tables 3 and 4, respectively. These parameters provide insights into the influence of ex ante variables on production parameters and the percentage of carcass weight distributed into each yield and quality grade category.

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[10] The Gaussian copula is essentially the same as what is observed in a multivariate normal distribution. Maintaining correlation allows us to evaluate the covariance structure between marginal distributions and also more accurately defines the simulation in order to preserve rank correlation relationships.

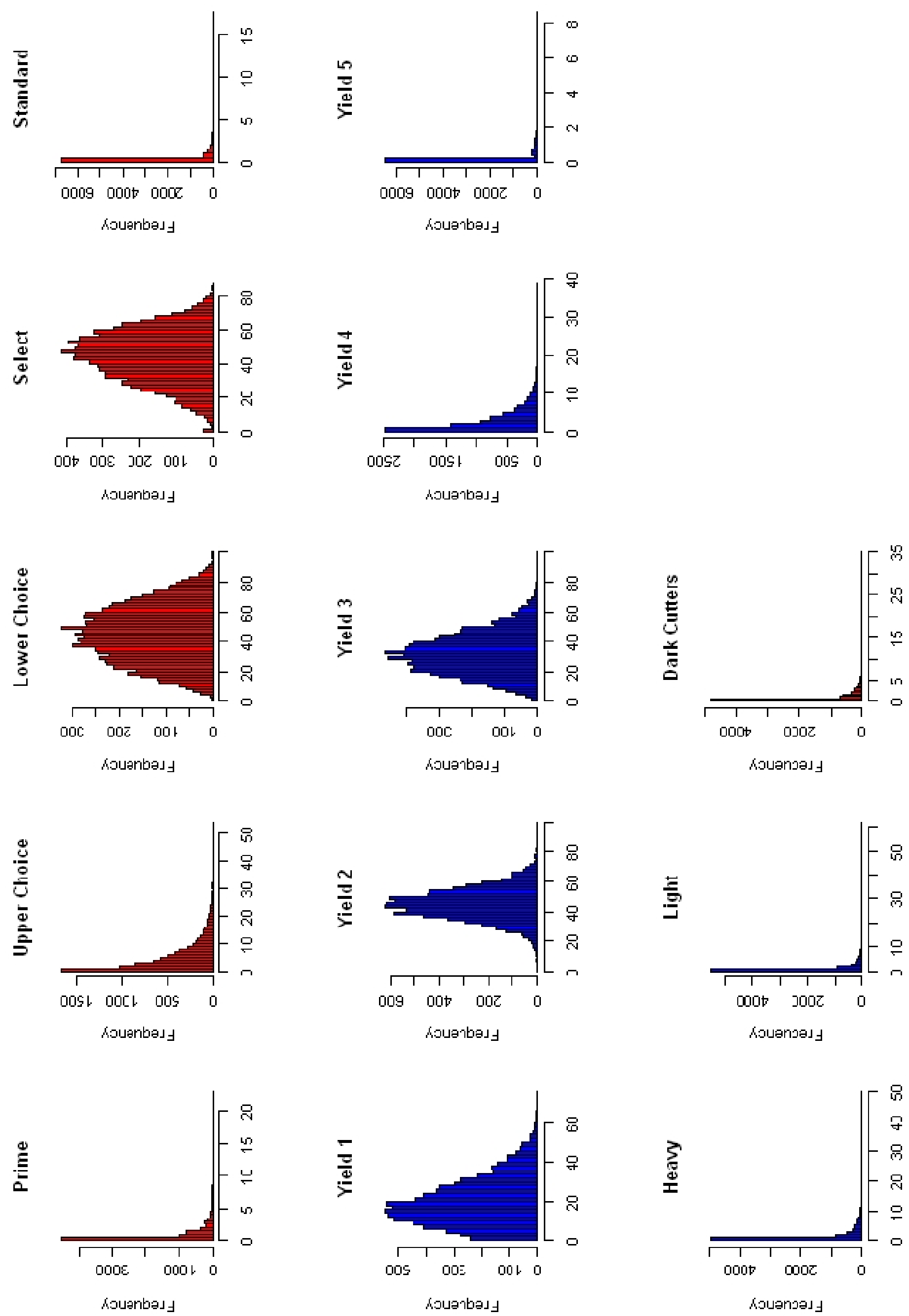

Figure 1. Histogram of percentage weight within each quality and yield grade category

Table 2. Summary Statistics for Fed Cattle Production (*N* = 7,706 pens)

					Censoring	
Variable	Mean	Std. Dev.	Minimum	Maximum	Observ.	Degree (%)
Performance Variables:						
DMFC	6.19	0.69	4.39	23.84	0	0.00
ADG	3.39	0.47	0.74	5.78	0	0.00
MORT	0.90	1.56	0.00	25.83	3,591	46.60
VCPH	11.45	6.19	0.03	60.00	0	0.00
Grade Variables:						
*PctYG*1	19.91	12.01	0.00	75.70	77	1.00
*PctYG*2	44.93	10.32	0.00	100.00	1	0.01
*PctYG*3	31.87	13.69	0.00	100.00	3	0.04
*PctYG*4	3.10	3.56	0.00	38.80	1,606	20.84
*PctYG*5	0.20	0.60	0.00	8.60	6,432	83.47
Quality Variables:						
PctPrime	0.90	1.64	0.00	22.60	4,212	54.66
PctUpperChoice	5.22	5.55	0.00	53.30	1,133	14.70
PctLowerChoice	45.05	18.46	1.70	100.00	0	0.00
PctSelect	44.49	14.93	0.00	87.50	27	0.35
PctStandard	0.20	0.67	0.00	17.40	6,586	85.47
Other Variables:						
PctDarkCutters	1.09	2.42	0.00	34.90	4,567	59.27
PctHeavy	1.71	3.44	0.00	50.00	4,165	54.05
PctLight	1.19	2.70	0.00	61.70	4,387	56.93
Independent Variables:						
Weight	756.70	93.17	500.00	1,000.00		
Proportion of Sample:						
Steers	0.53					
Mixed	0.13					
Kansas	0.86					
Winter	0.25					
Fall	0.26					
Spring	0.24					

Conditioning variables significantly impact the mean and variance of performance, yield grade, and quality characteristics. Seasonal and gender effects are statistically significant in many of the equations. In general, steers have a greater likelihood of attaining more desirable yield grades and less desirable quality grades relative to heifers, as shown by the significant positive parameter estimates for steers for *YG*1, *YG*2, and *Select*. The same is also true for pens with higher entry weights, as the coefficient on Log(*Wt*) was positive for *YG*1 and *YG*2, negative for *YG*3, and insignificant for *YG*4 and *YG*5. Log(*Wt*) was also negative for *Upper Choice* and *Lower Choice* and positive for *Select*. These findings confirm that heavier-weight feeder cattle, which tend to be on grain-fed diets for a shorter time, result in better yield grade but worse quality grade relative to lighter-weight placements.

Seasonal variation is clearly present for gender and placement weight, but somewhat less clear in performance, quality, and yield grades. For example, winter and fall placements show similar patterns regarding differences in quality, yield, and performance. Both fall and winter placed cattle have a higher proportion of *YG*1, a lower proportion of *YG*2, and a higher proportion of *Upper Choice* and *Lower Choice*, relative to summer placements. This result is consistent with findings reported by Kreikmeier and Mader (2004). In addition, Mader, Dahlquist, and Gaughan (1997) found that fed cattle exposed to mild-to-moderate cold temperature stress exhibit greater marbling (the main driver of higher quality grade). The biological relationship between climate and fat deposition in cattle feeding has not yet been resolved (Kreikmeier and Mader, 2004). Cattle placed on feed in the fall realize unfavorable performance effects, including higher feed conversion rates and lower average daily gain, relative to those placed in summer—which is consistent with animal science literature (e.g., Pusillo, Hoffman, and Self, 1991).

Accounting for the impact from conditioning variables is essential for generating the conditional mean and variance associated with each dependent variable. The large number of statistically significant variables indicates the importance of accounting for these variables when characterizing each dependent variable as a conditional random variable. In this way, we can obtain conditional distributional parameters from each variable that are unique for each different set of conditioning variables.

R^2 measures demonstrate the relative ability of each set of conditioning variables to describe variation in the dependent variable. For dependent variables that did not exhibit censoring, we use a typical R^2 measure:

$$R^2 = 1 - \frac{\Sigma(y_i - \hat{y})^2}{\Sigma(y_i - \overline{y})^2}.$$

For equations exhibiting censoring and thus requiring a Tobit model, we compute a pseudo-R^2 measure, as an ordinary R^2 measure can result in inaccurate goodness-of-fit measures. Veall and Zimmermann (1994) show how a modified pseudo-R^2 measure (based on McKelvey and Zavoina, 1975) outperforms other pseudo-R^2 measures, such as McFadden's likelihood ratio index. Their modified pseudo-R^2 measure can be written as:

$$R_{mz}^2 = \frac{\Sigma(\hat{y}_i^* - \overline{\hat{y}}_i^*)^2}{\Sigma\left[(\hat{y}_i^* - \overline{\hat{y}})^2 + \sigma_i^2\right]},$$

where $\hat{y}_i^*$ is the predicted latent variable, while $\overline{\hat{y}}_i^*$ is the mean of predicted latent variables. This particular pseudo-R^2 measure is favored because it is more robust than alternative measures and can closely replicate ordinary R^2 measures in situations where there is no censoring. Both goodness-of-fit measures are reported in table 3.

Next, we estimate Spearman rank correlation coefficients of the residuals to evaluate the covariance between production and quality measures as well as to validate the importance of using a multivariate simulation method. Simulated data must preserve the correlation structures to generate a consistent multivariate distribution. After estimating the conditional marginal density functions for each equation, the residuals are correlated across equations (table 5).

Cross-equation correlations exist due to unobserved variables such as weather, genetics, and cattle growing and preconditioning programs. As such, errors in yield grade equations tend to be correlated with errors in quality grade equations. The trade-off between quality and yield components is clearly nonlinear. For example, the rank correlation of errors with *YG*1 and *Prime*, *Upper Choice*, and *Lower Choice* is negatively correlated with a much stronger relationship between *Lower Choice* than *Prime*. This negative relationship demonstrates a

Table 3. Parameter Estimates for Marginal Density Mean Parameters (β)

	Performance				Grade				
Variable	*DMFC*	*ADG*	*MORT*	*VCPH*	*YG*1	*YG*2	*YG*3	*YG*4	*YG*5
Intercept	0.728*	−2.600*	19.747*	11.192*	−21.742*	40.955*	70.939*	6.439	−2.367
	(0.110)	(0.669)	(4.243)	(0.707)	(2.704)	(1.832)	(3.249)	(3.599)	(3.895)
Steers	−0.060*	0.298*	0.227	0.066*	3.374*	3.039*	−4.059*	−2.200*	−1.034*
	(0.006)	(0.041)	(0.238)	(0.020)	(0.317)	(0.331)	(0.690)	(0.180)	(0.453)
Mixed	−0.025*	0.166*	0.558	0.241*	3.326*	0.952	−2.429*	−0.582*	0.013
	(0.011)	(0.068)	(0.479)	(0.032)	(0.583)	(0.502)	(1.131)	(0.171)	(0.528)
Log(*Wt*)	0.181*	0.885*	−3.014*	−1.311*	4.823*	0.808*	−5.003*	−0.252	0.164
	(0.017)	(0.103)	(0.628)	(0.107)	(0.395)	(0.265)	(0.434)	(0.537)	(0.585)
Kansas	−0.100*	0.087	0.014	−0.254*	6.789*	−1.801*	−4.404*	−1.044*	−0.473
	(0.009)	(0.082)	(0.236)	(0.026)	(0.455)	(0.635)	(1.556)	(0.301)	(0.457)
Winter	0.007	−0.199*	0.246	−0.070*	3.482*	−2.459*	−0.428	−0.240	0.031
	(0.007)	(0.062)	(0.401)	(0.031)	(0.451)	(0.421)	(0.969)	(0.186)	(0.723)
Fall	0.059*	−0.219*	0.297	0.020	2.791*	−1.014*	−0.806	−0.378*	0.314
	(0.007)	(0.064)	(0.528)	(0.031)	(0.378)	(0.439)	(0.860)	(0.158)	(0.561)
Spring	−0.009	−0.063	0.057	−0.053	0.164	−2.971*	2.999*	0.487*	−0.014
	(0.007)	(0.063)	(0.373)	(0.031)	(0.442)	(0.402)	(0.911)	(0.179)	(0.487)
R^2	0.240	0.231	0.037 [a]	0.220	0.081 [a]	0.036	0.052	0.078 [a]	0.061 [a]

Notes: An asterisk (*) denotes estimate is statistically significant at the 5% level. Values in parentheses are block jackknife standard errors.

[a] Denotes that a pseudo-R^2 measure was used based on Veall and Zimmermann (1994).

(extended . . . →)

Table 4. Parameter Estimates for Marginal Density Variance Parameters (γ)

	Performance				Grade				
Variable	*DMFC*	*ADG*	*MORT*	*VCPH*	*YG*1	*YG*2	*YG*3	*YG*4	*YG*5
Intercept	0.139	0.250	2.396	−0.002	0.788	3.860*	4.788	0.236	−0.649
	(1.963)	(6.770)	(8.854)	(3.905)	(1.202)	(1.668)	(3.780)	(2.122)	(3.369)
Steers	−0.216	0.267	−0.126	−0.443*	0.244*	0.010	0.108	−0.316*	−0.101
	(0.115)	(0.139)	(0.212)	(0.125)	(0.050)	(0.060)	(0.094)	(0.097)	(0.302)
Mixed	0.244	0.491*	0.955*	0.136	0.345*	0.054	0.080	0.064	0.052
	(0.170)	(0.222)	(0.290)	(0.177)	(0.065)	(0.075)	(0.135)	(0.097)	(0.351)
Log(*Wt*)	−0.761*	−0.342	−0.166	−0.276	0.533*	0.146	0.052	0.439	0.274
	(0.289)	(1.020)	(1.351)	(0.589)	(0.183)	(0.254)	(0.577)	(0.327)	(0.514)
Kansas	−0.026	−0.050	0.353	0.146	0.204*	−0.214*	−0.127	−0.381*	0.498
	(0.176)	(0.223)	(0.318)	(0.116)	(0.070)	(0.068)	(0.104)	(0.123)	(0.354)
Winter	0.178	0.025	−0.286	0.016	0.395*	−0.117	0.164*	0.201	−0.010
	(0.149)	(0.187)	(0.318)	(0.122)	(0.064)	(0.064)	(0.080)	(0.108)	(0.448)
Fall	0.415*	0.399*	0.218	0.191*	0.297*	−0.005	0.096	−0.016	−0.224
	(0.161)	(0.193)	(0.314)	(0.094)	(0.066)	(0.063)	(0.081)	(0.115)	(0.386)
Spring	0.019	−0.120	−0.527	−0.133	0.133*	−0.014	0.095	0.233*	0.138
	(0.148)	(0.191)	(0.301)	(0.118)	(0.066)	(0.069)	(0.094)	(0.111)	(0.335)

Notes: An asterisk (*) denotes estimate is statistically significant at the 5% level. Values in parentheses are block jackknife standard errors.

(extended . . . →)

Table 3. Extended

	Quality					Other		
Variable	*Prime*	*Upper Choice*	*Lower Choice*	*Select*	*Standard*	*Dark Cutters*	*Light*	*Heavy*
Intercept	5.991	17.042*	165.741*	−14.085	−3.217	−1.095	−46.959	32.023
	(3.855)	(2.667)	(3.521)	(11.471)	(4.395)	(0.713)	(30.001)	(17.985)
Steers	−1.577*	−2.559*	−12.102*	9.799*	2.298	0.190	4.397	−3.027*
	(0.189)	(0.238)	(0.903)	(0.662)	(1.511)	(0.165)	(3.561)	(0.882)
Mixed	−0.662*	−1.452*	−6.937*	2.832*	0.909	−0.941*	2.338	−0.440
	(0.280)	(0.334)	(0.970)	(0.823)	(1.767)	(0.310)	(3.421)	(0.808)
Log(*Wt*)	−0.748	−1.203*	−15.382*	6.602*	−0.328	−0.015	6.968	−4.830
	(0.577)	(0.388)	(0.555)	(1.758)	(0.614)	(0.095)	(4.494)	(2.808)
Kansas	−0.734*	−4.145*	−16.043*	12.339*	1.168	0.249	−1.530	0.175
	(0.245)	(0.540)	(0.937)	(0.837)	(1.611)	(0.274)	(2.279)	(0.755)
Winter	0.429	1.419*	3.106*	−2.289*	0.389	−0.465*	−1.878	0.816
	(0.273)	(0.275)	(0.829)	(0.609)	(0.749)	(0.231)	(2.121)	(1.244)
Fall	0.479	1.452*	4.445*	−3.388*	−0.384	−0.466*	−2.454	0.776
	(0.274)	(0.261)	(0.778)	(0.599)	(0.818)	(0.224)	(2.246)	(1.140)
Spring	−0.106	0.165	1.563	0.366	0.663	0.194	−0.895	−0.175
	(0.287)	(0.248)	(0.966)	(0.707)	(0.741)	(0.224)	(1.923)	(1.445)
R^2	0.095 [a]	0.107 [a]	0.219	0.207	0.181 [a]	0.012 [a]	0.233 [a]	0.158 [a]

Table 4. Extended

	Quality					Other		
Variable	*Prime*	*Upper Choice*	*Lower Choice*	*Select*	*Standard*	*Dark Cutters*	*Light*	*Heavy*
Intercept	0.362	1.601	10.433*	2.489	−0.242	0.758	0.994	0.882
	(5.609)	(1.786)	(0.993)	(2.927)	(2.739)	(0.588)	(18.905)	(12.616)
Steers	−0.599*	−0.304*	0.076	−0.240*	−0.122	0.820*	0.712	−0.005
	(0.154)	(0.089)	(0.060)	(0.070)	(0.634)	(0.121)	(1.354)	(0.467)
Mixed	0.208	−0.120	−0.063	−0.178*	0.255	0.671*	0.644	0.472
	(0.174)	(0.122)	(0.072)	(0.069)	(0.758)	(0.191)	(1.311)	(0.362)
Log(*Wt*)	0.238	0.337	−0.762*	0.422	0.287	0.184*	0.251	0.186
	(0.848)	(0.271)	(0.151)	(0.444)	(0.454)	(0.090)	(2.903)	(1.926)
Kansas	0.026	−0.427*	0.134	−0.031	0.088	0.454	−0.269	0.832
	(0.198)	(0.089)	(0.115)	(0.083)	(0.707)	(0.252)	(0.635)	(0.494)
Winter	0.302	0.461*	0.116	0.089	0.156	−0.251	0.054	−0.425
	(0.222)	(0.105)	(0.068)	(0.077)	(0.421)	(0.167)	(0.601)	(0.517)
Fall	0.181	0.147	0.023	0.196*	0.431	−0.136	0.614	0.266
	(0.217)	(0.100)	(0.066)	(0.080)	(0.441)	(0.171)	(0.742)	(0.513)
Spring	0.284	0.226*	0.116	−0.025	−0.086	0.281	0.013	−0.254
	(0.251)	(0.114)	(0.071)	(0.066)	(0.398)	(0.177)	(0.617)	(0.532)

Table 5. Spearman Correlation Coefficients on Inverted Residuals in Margins

Variable	*YG*1	*YG*2	*YG*3	*YG*4	*YG*5	*Heavy*	*Light*	*DMFC*	*ADG*
Prime	−0.22	−0.11	0.22	0.24	0.35	−0.27	0.30	0.03	0.03
Upper Choice	−0.42	−0.11	0.38	0.26	0.08	−0.02	−0.03	−0.07	0.20
Lower Choice	−0.51	−0.14	0.48	0.27	0.07	0.08	−0.11	0.01	0.19
Select	0.37	0.18	−0.39	−0.24	−0.06	−0.06	0.04	−0.07	−0.10
Standard	0.10	−0.02	−0.04	−0.16	−0.44	0.44	−0.41	0.02	−0.03
Heavy	−0.07	−0.07	0.10	0.04	−0.35	—	—	—	—
Light	0.09	0.07	−0.12	−0.03	0.34	—	—	—	—
DMFC	0.08	0.02	−0.06	−0.05	−0.02	−0.14	0.15	—	−0.79
ADG	−0.22	−0.06	0.20	0.11	0.02	0.21	−0.19	—	—

Correlation Within Yield Grades

	*YG*1	*YG*2	*YG*3	*YG*4
*YG*2	0.07	—		
*YG*3	−0.76	−0.60	—	
*YG*4	−0.48	−0.46	0.54	—
*YG*5	−0.11	−0.12	0.11	0.29

Correlation Within Quality Grades

	Prime	*Upper Choice*	*Lower Choice*	*Select*	*Standard*
Upper Choice	0.34	—			
Lower Choice	0.33	0.63	—		
Select	−0.37	−0.53	−0.87	—	
Standard	−0.43	−0.13	−0.08	0.03	—

trade-off between high quality and yield grades. As quality grades decline with *Select* and *Standard*, the rank correlation with *YG*1 becomes positive. In general, desirable yield grades are positively correlated with low quality grades and negatively correlated with high quality grades. The converse also holds: high quality grades are positively correlated with poor yield grades and negatively correlated with superior yield grades.

This trade-off is not limited to quality components. Average daily gain (*ADG*) has a significantly negative relationship with *YG*1 and *YG*2, indicating faster weight gain is associated with poorer yield grade. However, *ADG* is positively correlated with high quality grades as indicated by the significant coefficients for *Upper Choice* and *Lower Choice* of 0.20 and 0.19, respectively. While the relationship with *DMFC* is not as clear with regard to quality grade, there is a positive relation between better yield grades and *DMFC*. This finding implies that less feed-efficient cattle (high *DMFC*) tend to attain superior yield grades. These trade-offs are important to consider within the context of providing incentives to cattle producers. A higher premium for *YG*1 may not immediately result in a higher proportion of meat graded as *YG*1; in order to achieve this, producers will likely have to settle for lower quality grades (i.e., fewer *Prime* and *Upper Choice*), lower *ADG*, and higher *DMFC*.

To fully characterize the joint distribution between the given equations, the next computational step involves estimating the parameters of the copula function that account for the correlation structure between equations as defined in equation (8). A joint density function can then be found based on the product of the conditional marginal distributions and a unique copula function. This joint density function can be simulated while maintaining the covariance structure between the random variables by recognizing the copula function. This is a critical step in identifying the amount of risk inherent with grid pricing. An important point to note is that we first simulate the predicted percentage in each grade based on the results presented in table 3. The grid structure is then specified as a second step. This step is important because there is wide variability in grid structures. It allows us to simulate profit variability based on sample grids to evaluate the sensitivity of risk to different grids. Additionally, it allows us to assess the risk associated with an assumed grid structure. Given that more than half of the equations are censored, the simulated values associated with censored equations are truncated at zero to simulate data while preserving censoring aspects. Although past studies have noted the additional risk components, none have disaggregated conditional risk to this extent to simulate profit and profit variability.

Price Risk

We utilize a profit function similar to the one used by Belasco (2008), with the addition of the grid pricing premium or discount as shown in equation (1). To that end, the fed cattle price received (p) is computed as the sum of the average price (p^y) and the premium/discount associated with grid pricing (p^p), which can be written as $p = p^y + p^p$, where

(9)
$$p^p = \sum_{m}^{10} p_m^p(PctQ_m) + \frac{1}{2}\, p_{Select}^p \left(PctQ_{Select} - PctQ_{Choice}\right)$$

such that p_m^p and $PctQ$ refer to the quality price premium and the percentage of carcass weight from each pen that fits into each quality type. Additionally, $m = 1, 2, ..., 10$ refers to quality types that include yield grades 1–5 (excluding yield grade 3 which contains no premium); quality grades including Prime, Upper Choice, Lower Choice, and Standard; as well as other discounted types such as Dark Cutters, Heavy Weight (> 950 lbs.), and Light Weight (< 550 lbs.). In this simulation the base price is set equal to the live cattle price (fed cattle price plus any basis difference), assuming 50% of the carcasses grade Select and 50% grade Lower Choice, both under yield grade 3 (similar to Riley et al., 2009).[11]

The incorporation of quality risk into profit variability occurs in two areas. The first relates to the a priori uncertainty of quality grades attained by each pen. The second area of quality risk relates to the fact that premiums and discounts are unknown at the time placement decisions are made. Thus, quality premiums and discounts are stochastic variables and the added variability introduces another reason why premiums for higher quality cattle may not lead to anticipated large supplies of high quality cattle. All production decisions are assumed to be made at the beginning of the feeding period to reflect the risk faced by the producer when cattle are placed on feed.[12] While decisions are made at the beginning of feeding, the premiums associated with all grades as well as the quality performance are unknown until the end of the production period.

[11] Since grid pricing structures are based on carcass weight, another element of risk to consider is the ratio between live weight and carcass weight or dressing percentage. In these data, this average dressing proportion was 0.6366 with a standard deviation of 0.0112, making it a relatively trivial area of risk compared to those analyzed here. Consequently, variation in dressing was not considered in this study.

[12] While feedlots frequently adjust feed rations and other practices through the feeding period, this analysis is focused on the risk associated with placing cattle when ownership is retained.

Table 6. ARIMA Forecast Selections and Results for Grid Pricing Premiums

	In-Sample			Forecast	
Quality Type	Model (P, I, Q)[a]	AIC	σ^2	Expected Price	Standard Error
Prime	(2, 0, 0)	935.23	0.25	7.81	1.18
Upper Choice	(5, 0, 1)	395.89	0.11	2.13	0.77
Select	(4, 0, 3)	1,868.00	1.04	−8.60	4.59
Standard	(3, 0, 1)	2,216.14	1.81	−19.63	3.29
*YG*1	(2, 0, 0)	−571.73	0.02	2.99	0.35
*YG*2	(5, 0, 4)	−1,311.45	0.01	1.29	0.18
*YG*4	(2, 1, 2)	792.21	0.20	−11.93	1.73
*YG*5	(4, 0, 2)	1,044.20	0.29	−19.25	1.12
Dark Cutters	(3, 0, 3)	1,955.09	1.19	−31.71	2.02
Light	(5, 0, 3)	1,505.20	0.59	−20.35	1.12
Heavy	(5, 1, 3)	1,045.92	0.29	−11.69	1.89

[a] P, I, and Q denote the number of autoregressive terms, number of differences, and number of lagged forecast error terms, respectively.

To characterize this temporal element of risk, we estimate the probabilistic characteristics of these premiums.[13] Using nearly 13 years of average weekly grid pricing data reported by USDA/AMS, optimal ARIMA models are selected based on Akaike information criteria (AIC) and fitted to each first-differenced and deseasonalized premium price series after being lagged for 20 weeks.[14] Forecasts were then made 20 weeks out (the typical feeding horizon) to assess the predicted premium as well as the uncertainty around this forecast. Seasonal components were then added back into the predictions, which are reported in table 6.

Profit Variability

Using the procedure developed by Phoon, Quek, and Huang (2004) (henceforth PQH), expected prices and standard errors reported in table 6 were used to simulate normally distributed deviations from expected prices that preserve rank correlation between grid price deviations. This procedure allows for the simulation of correlated random variables from mixed marginal distributions. The PQH procedure has been shown to perform with greater accuracy than the more frequently used Iman and Conover (1982) procedure in simulations of higher order multivariate distributions (Anderson, Harri, and Coble, 2009).

Expected corn prices are assumed to be \$3.32 per bushel with an implied volatility of 29.2%, while expected cattle prices are assumed to be \$88.58 per cwt with an implied volatility of 25.0%. While the live cattle price is based on an August settlement price, which is the anticipated sell date, corn is based on a May settlement price, which is midway through the feeding period. Implied volatility is computed based on the generalized Black-Scholes formula that uses option premium information. To simulate the joint distribution for corn and live cattle prices, we again use the PQH procedure based on historical cash price data to preserve rank

[13] Typically, information from the futures and options markets can be used to obtain expected mean and variance parameters for prices. However, in the absence of these markets, we estimate the grid price premiums/discounts.

[14] Each premium price series was deseasonalized based on the difference between the weekly average across 13 years and the 13-year price mean. The deseasonalized series were then first-differenced before computing optimal ARIMA parameters.

correlation. Based on these price components, we simulate a hypothetical steer pen placed on feed in Kansas for five months in spring with an average placement weight of 750 pounds.

There are two sources of uncertainty in the total premium received from grid pricing: the value associated with each grade (premium/discount), and the amount of carcass weight that falls into each grade. With this in mind, we simulate three scenarios:

1. Pricing on a grid with uncertainty in both premiums/discounts and grades,
2. Pricing on a grid with fixed premiums/discounts and grade uncertainty, and
3. Average pricing.

We run two different simulations (with and without corn and cattle price risk) with three scenarios to evaluate the impact of price risk on the magnitude of quality risk. Following Belasco (2008), we assume forward contracts are used to remove risk associated with cattle and corn prices.

Results from the first simulation (no corn and cattle price risk) indicate that grid pricing increases profit variability by 21.5% in comparison to when no price risk is involved. This is found by taking the difference between scenarios 1 and 3. Of this increased variability, an increase of 20.6% can be attributed to uncertainty in quality grading, while the remainder (0.9%) can be attributed to grid price risk,[15] which is found by taking the difference between scenarios 1 and 2. In the next simulation, where price risk is fully incorporated, quality risk plays an almost unnoticeable role by increasing the standard deviation in profits by 0.8%. These results are consistent with the findings of Harri et al. (2009), who compute optimal hedge ratios under grid pricing and average pricing and find that grid pricing risk is relatively small when no hedging is used.[16]

The distribution of premiums and discounts from this set of simulations is shown in figure 2. A risk premium is usually embedded in taking on additional risk, which in this case is a mean of implied quality premiums ($1.73 per cwt with a standard deviation of $2.54 per cwt). Figure 2 illustrates a slightly asymmetric distribution of premiums and discounts where the 25th and 75th percentiles correspond to 0.08 and 3.40, respectively. Within the context of price risk, this variation is minimal given the implied volatility typically associated with fed cattle prices.

To evaluate the sensitivity of our results to other grid specifications, we compare these results to two different grids. While the original grid allows us to evaluate the average premiums/discounts received, it is important to validate its consistency with other representative grids. First, we use a representative grid that provides stronger incentives for higher quality grades as provided by U.S. Premium Beef (USPB) (an example grid can be found at their website www.uspremiumbeef.com).[17] A second grid considered is offered by Angus GeneNet (www.genetbeef.com/grid.pdf),[18] which provides stronger incentives for high yield

[15] It is important to note that these results are dynamic in the way they change when the price levels and associated volatilities change over time. However, the prices used in this study reflect the current state of each market.

[16] Harri et al. (2009) justify this result with the finding of a negative correlation between revenues from base prices and revenues from premiums and discounts. They show empirically that increases in the variance of premiums and discounts result in reduced overall revenue variance.

[17] Stronger incentives are provided by higher premiums for Prime and Upper Choice that are about twice as large as the grid presented in table 1. Further, yield grade premiums/discounts are only provided on the positive difference between the pen percentage and the weekly average across USPB plants. In this analysis, we use their base grid, which is the most commonly used.

[18] The GeneNet grid provides stronger yield incentives by aligning quality grades with the grid in table 1 and enhancing premiums and discounts associated with all yield grades. Additionally, the discount associated with yield grade 4 is equal to the percentage of carcass in that grade (i.e., if 5% grades YG4, then the discount is equal to $5.00).

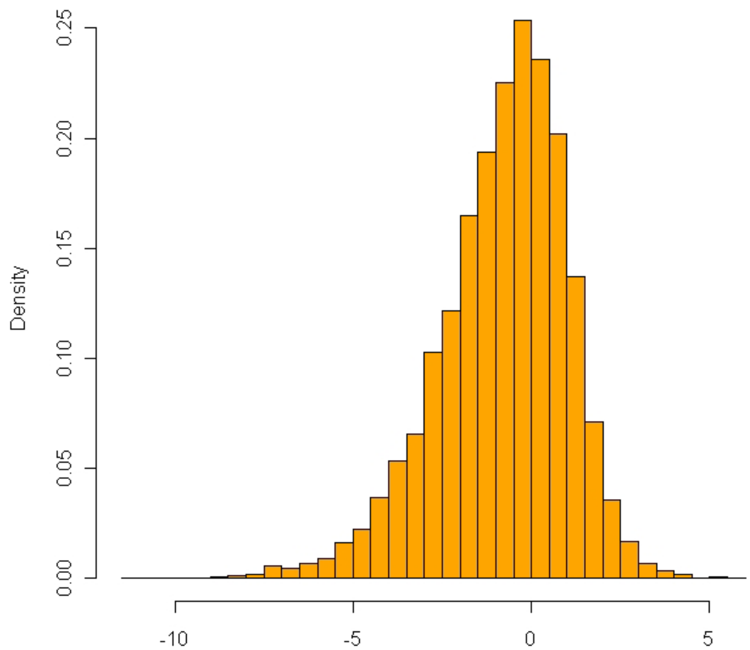

Figure 2. Histogram of premiums associated with simulation

grades and large penalties for inferior yield grades. Pricing on these grids reduces overall profit variability because incentives are focused only on a single quality type (yield or quality grade) and reduces the additional risk from pricing on a traditional grid by 20%–50% from the previous baseline scenario.[19]

The final part of this analysis uses in-sample data to evaluate the premiums that would be received assuming the grid in table 1. These hypothetical premiums ($ per cwt) are then ordered and placed into quintiles. Within each quintile, we take the mean of all relevant variables in table 7 to examine how changes to these variables are correlated with the hypothetical premium received in table 1. Within the lowest quintile, we see a discount of $2.31 per cwt, which is associated with a high proportion of meat in yield grade 1, a low proportion graded as Prime, and large discounts. The average discount applied to this group is statistically different from all other group mean discounts/premiums, based on a difference-in-means test. As we move to higher premium quintiles, some distinct relationships emerge. First, *DMFC* gets less efficient and cattle put on weight at a slower rate. This maintains our original hypothesis that quality and quantity measures are negatively related. Also, the distinction between *Lower Choice* and *Select* is important as *Select* accounts for more than 50% of the lowest two premium quintiles, while *Lower Choice* accounts for more than 50% of the top two premium quintiles. Conditioning variables are also correlated with premiums. For example, the lowest quintile contains 68% steer pens, while heifer pens dominate in higher premium pens. Season of placement also has an impact, as winter and fall placements are more likely to have higher premiums. These results provide important insights into how producers can use different characteristics to maximize premiums.

[19] The results reported above were consistent across simulations where conditioning variables were adjusted.

Table 7. Mean Statistics by Grid Premium Subsidy Quintile

Variable	Quintile 1	2	3	4	5	Statistically Equal Quintile Means [a]
Premium	−2.31	−0.71	0.17	1.07	2.52	
Dependent Variables:						
DMFC	1.80	1.81	1.81	1.82	1.84	12, 23
ADG	3.43	3.40	3.40	3.36	3.34	12, 13, 23, 45
MORT	1.09	0.95	0.92	0.82	0.72	23, 34
VCPH	2.36	2.34	2.34	2.33	2.29	12, 13, 23, 24, 34
***Proportion of Weight* (*out of 100*):**						
*PctYG*1	22.00	22.57	21.26	18.26	15.44	12, 13
*PctYG*2	43.36	45.40	45.33	45.34	45.21	23, 24, 25, 34, 35, 45
*PctYG*3	30.68	28.95	30.24	33.11	36.36	13
*PctYG*4	3.66	2.88	2.98	3.12	2.85	23, 25, 34, 35
*PctYG*5	0.31	0.20	0.19	0.17	0.14	23, 24, 34, 45
PctPrime	0.34	0.40	0.69	0.99	2.08	12
PctUpperChoice	1.99	2.68	4.27	6.50	10.64	
PctLowerChoice	27.58	33.55	42.95	53.39	67.73	
PctSelect	56.01	53.65	47.22	39.31	26.31	
PctStandard	0.44	0.29	0.14	0.08	0.04	
PctDarkCutters	2.97	1.02	0.73	0.48	0.28	
PctHeavy	3.42	1.84	1.45	1.08	0.75	
PctLight	2.24	1.07	0.98	0.91	0.74	23, 34
Independent Variables:						
Weight	772.78	765.09	749.95	735.10	727.78	
***Proportion of Subsample* (*out of 100*):**						
Kansas	96.17	93.45	87.80	79.75	72.36	
Steers	68.27	62.23	55.48	44.97	35.04	
Mixed	12.07	11.62	14.67	14.08	12.65	12, 14, 15, 25, 34, 35, 45
Winter	17.20	23.23	27.06	26.93	28.55	34, 35, 45
Fall	20.05	23.49	25.76	27.38	31.08	23, 34
Spring	31.02	27.58	20.96	21.67	16.87	34

[a] Differences in quintile means are based on difference-in-means test. For example, “12” indicates the means from quintiles 1 and 2 are not statistically different.

Concluding Comments

Results from simulations add information regarding the degree to which quality risk augments existing profit variability for cattle feeders. When full price protection measures are taken, the introduction of quality and yield risk increases the standard deviation of expected profit by over 20%. Most of this variation comes from uncertainty around quality grading. This increase in profit variability reflects the ineffectiveness of existing risk management tools in managing price risk under grid pricing. Alternatively, when no price protection measures are taken, the relative amount of risk from grid price risk is hardly noticeable. Taken together, these two scenarios identify another obstacle to more widespread usage of grid pricing. For cattle producers seeking to minimize risk through full price protection, grid pricing adds a large element of risk that is likely to be avoided by risk-averse producers. Alternatively, cattle producers who are less risk averse and avoid price protection are not likely to price on a grid either, since additional payoffs are relatively small. While these two examples are extreme, they illustrate that the demand for price protection and grid pricing are not complementary.

Another hypothesis posited in this study is that there is a significant trade-off between yield, quality, and performance measures within certain ranges. As demonstrated by an analysis of rank correlations and quintiles, significant trade-offs exist between yield and quality grades, as well as production (*DMFC* and *ADG*) indicators and yield grades. Our results confirm the use of grid pricing has not increased in the cattle-feeding industry in the past several years. In addition, our findings may also explain why grid pricing has not generated expected changes in higher quality cattle production.

The methods used in this research are widely applied in other fields and can be effectively utilized when dealing with other commodities and the trade-off between quality and yield risk. The estimation of a high dimension system of equations with a high degree of censoring has been limited in past studies but can be consistently and efficiently characterized and estimated, as is demonstrated in this study.

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